Study on the Change of People's Sentiment Towards COVID-19 and Its Influencing Factors based on NLP Technology

Chenyi Huang[1,*], Longtian Ye[2], Mingji Xi[3], Tian Wu[4]

[1]HEC Montreal, University de Montreal, Montreal, H3T 2A7, Canada, Chenyi.huang@hec.ca
[2]department of Computer Science, University of North Carolina at Chapel Hill, Chapel Hill, 27514, United States, longtian@ad.unc.edu
[3]Department of Science, Virginia Polytechnic Institute and State University, 24060, United State, ximingji200312@vt.edu
[4]Department of Mathematics/ Department of Economics & Business, Cornell College, Iowa, 52314, United State, twu23@cornellcollege.edu
*Corresponding author

Abstract. This paper explores the influencing factors of people's sentiments towards the covid pandemic. A LSTM (Long Short Term Memory) network was used to determine sentiment scores of covid related tweets at certain time points. Regression analysis was used to evaluate the relationship between sentiment scores and the possible factors, including features of the virus itself and the stringency of government policies towards it. Our findings show that: (1) The public's sentiment scores are negatively correlated to lethality of the prevailing variants of the virus. (2) The variants' transmissibility had minor connection with polarized sentiments. (3) People's sentiments are positively related to relaxed stringency in 2022, which is different from the initial stage of pandemic when people were positively backing strict containment measures.

Keywords-Coronavirus, policies, machine learning, LSTM.

1. Introduction

More than two years has passed since the initial outbreak of COVID-19 in Wuhan, China. In January 2020, the lethal and contagious pneumonia caused by the covid began to spread in China. It was in late January when the pathogen was genetically sequenced and thus officially identified.

It is notable that people's attitude towards covid and related policies has been changing as the pandemic develops (Barkur et al. 2020). In this study, we were to probe into this gradual variation of sentiment quantitatively using natural language processing techniques, and determine what could be the driving factors that have led to this trend.

We scoped our study to three factors that seemed the most likely to influence people's sentiments due to their prevalence in mainstream conversations: **fatality** and **infectivity**, and measures taken by the government. The coronavirus is subject to mutations and already has more than ten variants until now, including the famous Delta and Omicron strain, while the fatality and infectivity vary for each variant. As for policies, the containment measures vary for countries and regions and has been a subject for considerable debate.

The correlation between people's sentiments and the above variables was explored using regression analysis. We hope that the results could help **understand the general public's feelings and concerns** quantitatively, and contain a grain of truth for reference when it comes to **taking actions towards similar pandemics.**

2. Literature review

A fundamental step of sentiment classification (SC) is the preprocessing of raw data sets. Preprocessing involves a series of techniques which cleans and prepares the corpus of data appropriately for next phases of elaboration, to achieve better performances. Indeed, a number of these techniques are exposed in the work of Agarwal et al. (2014) which concerns the sentiment classification of news headlines using Sentiwordnet lexicon. Specifically, the Natural Language Processing Tool (NLTK), a python library, is used for word tokenization, and POS (Part of Speech) - Tagging, Lemmatization and Stemming. Output of NLTK is fed to *SentiWordNet* (Sentiment dictionary) to determine if the headline belongs to the positive or negative class. Haddi, Liu and Shi (2013) noted that online texts usually contain lots of noise and uninformative parts, such as HTML tags, scripts and advertisements. These explanatory variables increase the dimensionality of the problem and makes the classification process more difficult. Other algorithms used to polish data that comes from Twitter messages include tokenization, and removal of Stop Words (An important tool in NLP used to improve the quality and reduce the dimension of text features). Saif et al. (2014) found that dynamically generated Stop Words lists perform better in reducing noise and data sparsity as opposed to the pre-compiled ones. Basic cleaner, slang conversion and negation replacement are also used.

While the existing algorithms of sentiment analysis and feature selection are mature, enhancement attempts remain an open field for research. Among the attempts, Naïve Bayes, and Support Vector Machines (SVM) are the frequently, if not most, used machine learning approaches for solving SC problems (Medhat et al. 2014). As noted by Medhat (2014), the Naïve Bayes classifier is simple and fast for implementation but does rely on the assumption of independence, a lack of which could cause serious classification accuracy problems. On the other hand, SVM attempts to determine good linear or non-linear boundaries between different classes, allowing them to accurately classify reviews in terms of quality (Medhat 2014). Another distinct, yet sophisticated technique is what we called Neural Network (NN). Despite having a more complex training process consequent on its nature as a multi-layer propagation, Moraes and Valiati (2013) argued that NN outperforms SVM regarding sentiment analysis accuracy over an empirical dimension. Wang et al. (2018) also proposed a capsule model based on Recurrent Neural Networks (RNN), a technique capable of outputting words with sentiment tendencies without using any linguistic knowledge, enhancing the performance to new levels.

Followed by a general understanding towards existing techs, we attempted to further our insights from previous works. Indeed, some works employed topic models in tweets to analyze different concerns about COVID-19. Dubey (2020) organized tweets ranging from 11th March to 31st March 2020 and explored the reactions towards the virus under twelve distinct cultural backgrounds. With the help of the NN model, he classified tweet sentiments into fear, joy, anticipation, anger, disgust, sadness, surprise, trust and found that different countries express different degrees of negative sentiments. Besides, Lyu et al. (2020) extracted Chinese Weibo posts to monitor public emotions and utilized three methods LSTM, BERT, and ERNIE (commercial deep learning API from Baidu Ltd) for sentiment classification, where the latter received the most noteworthy accuracy. However, ERNIE’s accuracy is perhaps owing to the language content. The study concluded that news and public events influence sentiments greatly and user’s sentiment tend to evolve over time: negative sentiments decrease, gratitude increase (Lyu et al. 2020). Likewise, Gupta et al. (2020) investigated sentiment towards lockdown measures in India during the pandemic and mentioned that China’s nationwide lockdown policy influenced India’s policy making. The tweets were extracted under the keywords #IndiaLockdown and #IndiafightsCorona; after using eight different classifiers including SVC and comparing them using precision, the results revealed that people show more positive attitudes towards the country's policy, but as time goes by, this trend diminishes. Nemes and Kiss (2020) used RNN to study the emotions on tweets and compared the results with TextBlob. While both methods delivered stable results, TextBlob had 30% more neutral results than the RNN model, and thus was not as useful for further evaluations (Nemes and Kiss 2020). While all the previously mentioned works help us establish a research framework, most substantial studies focus on the comparison in precision between current models, leaving the practical value of sentiment analysis ambiguous, if not undefined. Therefore, we shifted our emphasis into evaluating the application of sentiment analysis regarding the pandemic.

When it comes to social studies, we could not help noticing that different countries formulate different subsequent actions when tackling the Covid-19 pandemic. For example, in countries like India, Canada, Pakistan, Norway and China, more people supported the government lockdown policy as compared to regions in North America (Imran et al. 2021). Also, Hou et al. (2020) found that public risk perception and negative sentiments (such as depression, anxiety, and frustration) were highly correlated with the implementation of containment measures. That is, stricter measures were followed by a more negative marked sentiment. Other findings include delayed release of information which could ignite negative public emotions, whereas early implementation of appropriate containment measures and timely clarification of rumors could effectively reduce public anxiety and irrational behaviors. Nonetheless, prolonged containment measures could lead to decreased risk perception, increased negative sentiments, and fatigue with sustaining containment measures (Hou 2020). These findings and all similar society study across time could contribute to our conclusion, forming a reference for public sector policies makers.

3. Dataset

3.1. Requests and plan for data

The data for sentiment analysis is provided by Kaggle, Co., a data science oriented subsidiary company of Google LLC, who triumphs on its rich experience in cloud-based workspace for data science as well as Artificial Intelligence education.

Besides the text body of each covid related tweet as the essential input variable under the request of our research question, we were looking for the date of each tweet and their IP territory or country status. The dates allowed us to exclusively trace the factors of interest, like the number of infected persons and deaths, on that very day. The location information, on the other hand, helps us narrow down the regional anti-epidemic policies to the exact country so that we would have a clearer target.

3.2. Data in hand

Table 1: Dataset overview

Variables	Data Type	Descriptions
created_at	Datetime	Created time of the Tweets
text	Varchar	The raw text of the Tweets
location	Varchar	The region of the Tweets
hashtags	Varchar	Possible hashtags
followers_count	Int	Numbers of the followers
favourites_count	Int	Numbers of the favorites
description	Varchar	Details of the Tweet's owner
retweet_count	Int	Retweets number of current Tweets
retweet_favorite_count	Int	Number of likes of the retweets

The first dataset we found contains tweets from January 2020 to May 2022, with dates of the tweets, positions, raw text, and a series of valuable variables. (Table 1).
We also reserved the quantity of the followers and favourites of the tweets, so it could function as a threshold to determine the significance of tweets. (Table 2)

Table 2: Dataset snapshot – Text for sentiment analysis

created_at	location	hashtags	followers_count	favourites_count	retweet_count	retweet_favorite_count
1/24/2020 21:00	San Juan, USA	Null	15	323	1535	1718
1/24/2020 21:00	Charlotte, NC	Null	44	3648	0	0
1/24/2020 21:00	Madison, WI	Null	471	400	0	0
1/24/2020 21:00	Blue dot in red SC	Null	6667	33344	36	33
1/24/2020 21:00	Houston, TX	BREAKING fox5atl	1152	60793	6	2
1/24/2020 21:01	Upstate NY	Null	364	6951	757	1091
1/24/2020 21:01	Marietta, GA	Null	10849	166426	1	1
1/24/2020 21:01	Kent, WA	Null	1384	19375	181	1288
1/24/2020 21:01	Tennessee, USA	Null	718	56334	1	0
1/24/2020 21:01	Connecticut, USA	Null	45241	197818	91	43
1/24/2020 21:01	Miami, FL	Null	551	0	0	0
1/24/2020 21:01	Sioux Falls, SD	China Pakistan	1049	18209	17	28
1/24/2020 21:01	California, USA	Null	2169	17516	258	344
1/24/2020 21:02	Dallas, TX	Null	283	45090	2769	13976
1/24/2020 21:02	Maysville, KY	Null	910	14301	53	72
1/24/2020 21:02	Hastings, NE	Null	920	129021	95	425
1/24/2020 21:02	In the here and now USA	Null	5566	22569	1	3
1/24/2020 21:02	California, USA	Null	126	3573	0	0
1/24/2020 21:03	San Juan, USA	BreakingNews coronavirus	15	323	646	525
1/24/2020 21:03	Virginia, USA	Null	21254	15890	141	103
1/24/2020 21:03	Dallas, TX	Null	918	269	0	0
1/24/2020 21:03	Durham, NC	Null	160	170	1	0
1/24/2020 21:03	Topsail Island, NC	Null	4984	58641	8	9
1/24/2020 21:03	California, USA	Null	1242	7338	10	14
1/24/2020 21:03	California, USA	Null	218	86749	204	256

We also applied a list of countries and what kind of policies they applied to the citizens. So, analysis about the correlation between policies and virus features (Table 1) can be conducted. This dataset is collected and updated by Oxford Martin School, University of Oxford (cited from official website). Particularly, as shown in Figure 1, we applied the *Containment and Health Index* to determine the exact policy that came to effect to date.

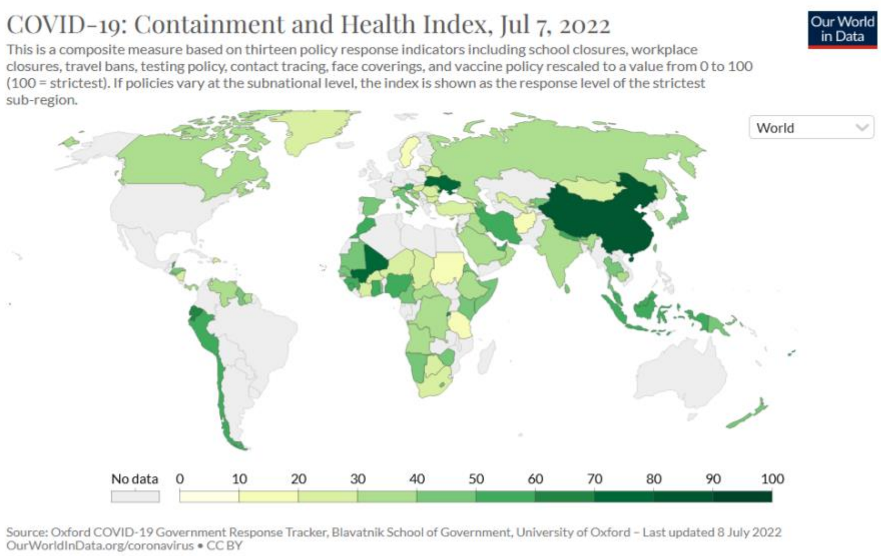


Figure 1: Factors for causality analysis (Oxford COVID-19 Government Response Tracker, 2022)

4. Methodology

This section describes procedures taken to determine people's attitude towards the pandemic and its influencing factors, which proposes the determination of sentiments using a Long Short-Term Memory (LSTM) network on tweets related to covid. LSTM is a variant of the Recurrent Neural Network (RNN) that is specialized for language processing. It requires vectors as inputs, which impelled us to preprocess the tweets and vectorize them with the procedure shown in the following flow flowchart (Figure 2), so that they could be accessed by the LSTM.

After that, a causality analysis is performed on the sentiments obtained, for the investigation on possible variables that are most influential to the former.

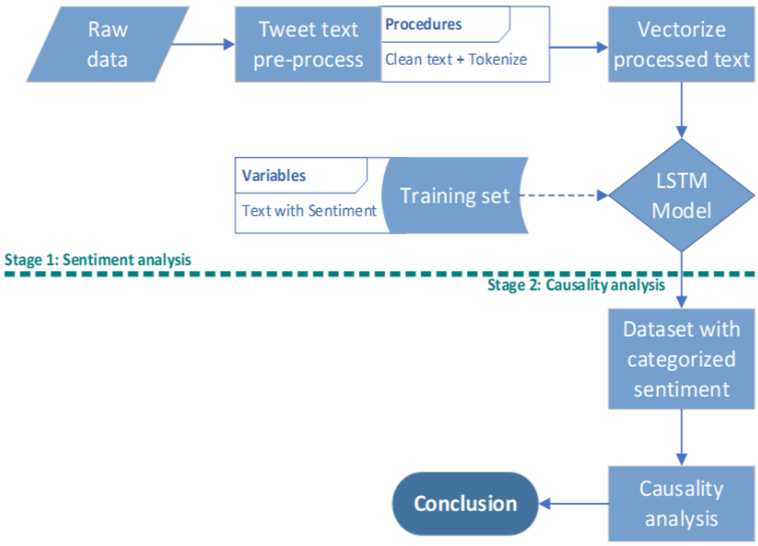


Figure 2: Main workflow of methodology

4.1 Tweet text preprocess

As deep networks require their inputs to be vectors and raw text cannot be fed directly into a LSTM, vectorizing the tweets became a necessity. This conversion was achieved with the following steps.

The tweets are first filtered using regex, where all the links and non-English characters are dropped, except for the hashtags and certain emoticons. The cleaned texts are then being checked for spelling mistakes (Figure 3) to eliminate the impact of human errors. Although most mainstream social media are born with auto spelling checks, it would not hurt to have control over the variables. Finally, the stopwords in the texts are then picked out using the nltk library of Python. Stopwords are the most frequent words in a language, such as "and" and "the". As minimal sentiments are carried by these words, they are removed to save memory and give more focus on the important information. The preprocessed texts are then vectorized using Glove, so that they could be fed into the LSTM.

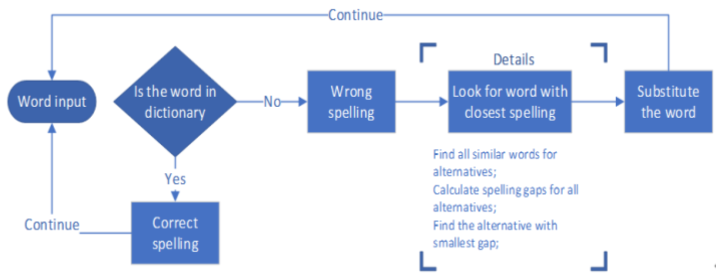


Figure 3: A Greedy Algorithm that corrects spelling mistakes

4.2 Sentiment classification with LSTM

After the completion of cleaning and vectorization, the data was passed into a LSTM network for the sentiment classification (Figure 4).

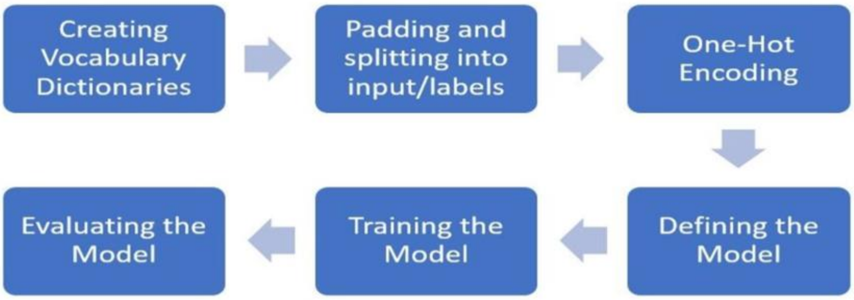


Figure 4: Preprocessing steps before LSTM model

LSTM was chosen for the classification task over other heuristic or machine learning approaches, because RNN and its descendants are among the most efficient models in dealing with natural language thanks to their ability in utilizing contexts, while LSTM resolves the problem of vanishing gradients for traditional RNNs.

The training of neural-networks is based on gradients, and vanishing gradient is the phenomenon of a model's gradients becoming very small in certain layers, preventing the model from further training. This problem is especially common in RNNs. LSTM are able to overcome it with many nonlinear layers, while being capable of holding on to longer term dependencies when classifying texts, making it the most suitable for this task of determining sentiments for tweets.

Implementation of the network was done under the PyTorch framework. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The data feeding into the LSTM gates are the input at the current time step and the hidden state of the previous time step. They are processed by three fully connected layers with a sigmoid activation function to compute the values of the input. Formally, it is supposed that there are h hidden units, the batch size is n, and the number of inputs is d. Thus, the input is $\mathbf{X}_t \in \mathbb{R}^{n\times d}$ and the hidden state of the previous time step is $\mathbf{H}_{t-1} \in \mathbb{R}^{n\times h}$. Correspondingly, the gates at time step t are defined as follows: the input gate is $\mathbf{I}_t \in \mathbb{R}^{n\times h}$, the forget gate is $\mathbf{F}_t \in \mathbb{R}^{n\times h}$, and the output gate is $\mathbf{O}_t \in \mathbb{R}^{n\times h}$. They are calculated as follows:

$$\begin{aligned}
\mathbf{I}_t &= \sigma(\mathbf{X}_t\mathbf{W}_{xi} + \mathbf{H}_{t-1}\mathbf{W}_{hi} + \mathbf{b}_i),\\
\mathbf{F}_t &= \sigma\left(\mathbf{X}_t\mathbf{W}_{xf} + \mathbf{H}_{t-1}\mathbf{W}_{hf} + \mathbf{b}_f\right),\\
\mathbf{O}_t &= \sigma(\mathbf{X}_t\mathbf{W}_{xo} + \mathbf{H}_{t-1}\mathbf{W}_{ho} + \mathbf{b}_o).
\end{aligned}$$

The $\mathbf{W}_{xi}, \mathbf{W}_{xf}, \mathbf{W}_{xo} \in \mathbb{R}^{d\times h}$ and $\mathbf{W}_{hi}, \mathbf{W}_{hf}, \mathbf{W}_{ho} \in \mathbb{R}^{h\times h}$ are weight parameters and $\mathbf{b}_i$, $\mathbf{b}_f$, $\mathbf{b}_o \in \mathbb{R}^{1\times h}$ are bias parameters. In order to update the state, a tanh layer creates a vector of new candidate values, $\tilde{\mathbf{C}}_t$, that could be added to the state (Figure 5). The details of Candidate Memory Cell $\tilde{\mathbf{C}}_t$ is illustrated as follow:

$$\tilde{\mathbf{C}}_t = \tanh\left(\mathbf{X}_t\mathbf{W}_{xc} + \mathbf{H}_{t-1}\mathbf{W}_{hc} + \mathbf{b}_c\right),$$

where $\mathbf{W}_{xc} \in \mathbb{R}^{d\times h}$ and $\mathbf{W}_{hc} \in \mathbb{R}^{h\times h}$ are weight parameters and $\mathbf{b}_c \in \mathbb{R}^{1\times h}$ are bias parameters.

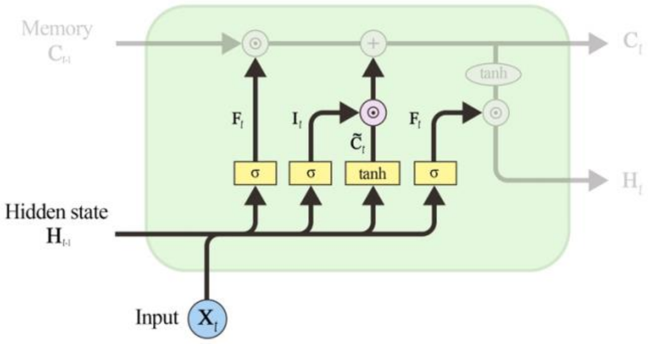


Figure 5: Computing the candidate memory cell in an LSTM model

Based on the above-mentioned components, we use the input gate $\mathbf{I}_t$ governing how much we take new data into account via $\tilde{\mathbf{C}}_t$, and the forget gate $\mathbf{F}_t$ addressing how much of the old memory cell content $\mathbf{C}_{t-1} \in \mathbb{R}^{n\times h}$ we retain. Thus, we arrive at the following updated equation:

$$\mathbf{C}_t = \mathbf{F}_t \odot \mathbf{C}_{t-1} + \mathbf{I}_t \odot \tilde{\mathbf{C}}_t,$$

and a graphical illustration of the data flow up to the present is shown in Figure 6.

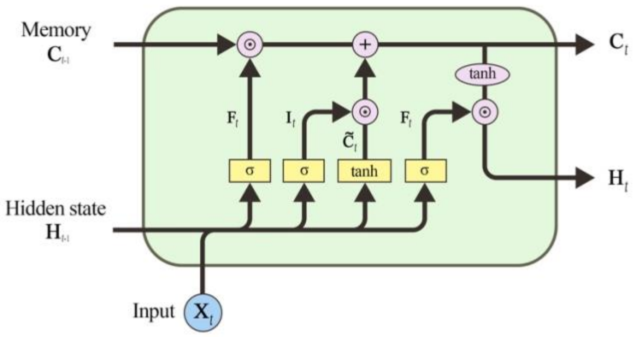


Figure 6: Computing the memory cell in an LSTM model

Finally, we need to use the output gate to compute the hidden state $\mathbf{H}_t \in \mathbb{R}^{n\times h}$. It is simply a gated version of the tanh of the memory cell,

$$\mathbf{H}_t = \mathbf{O}_t \odot \tanh(\mathbf{C}_t).$$

When the output gate approximates 1 we effectively pass all memory information through to the predictor, whereas for the output gate close to 0 we retain all the information only within the memory cell and perform no further processing. The whole chain structure of LSTM is shown in Figure 7.

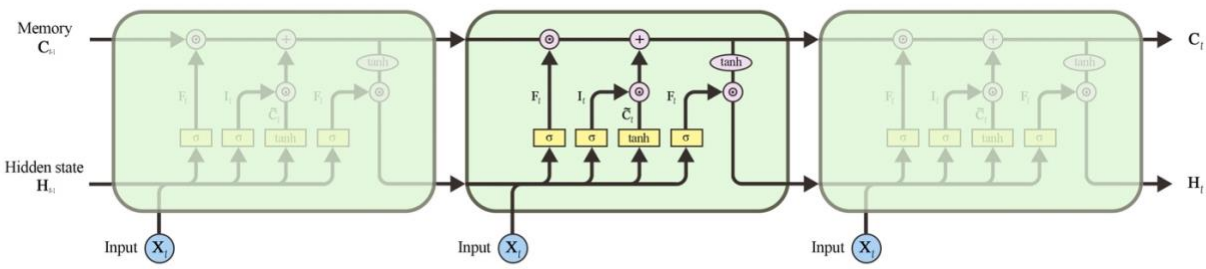
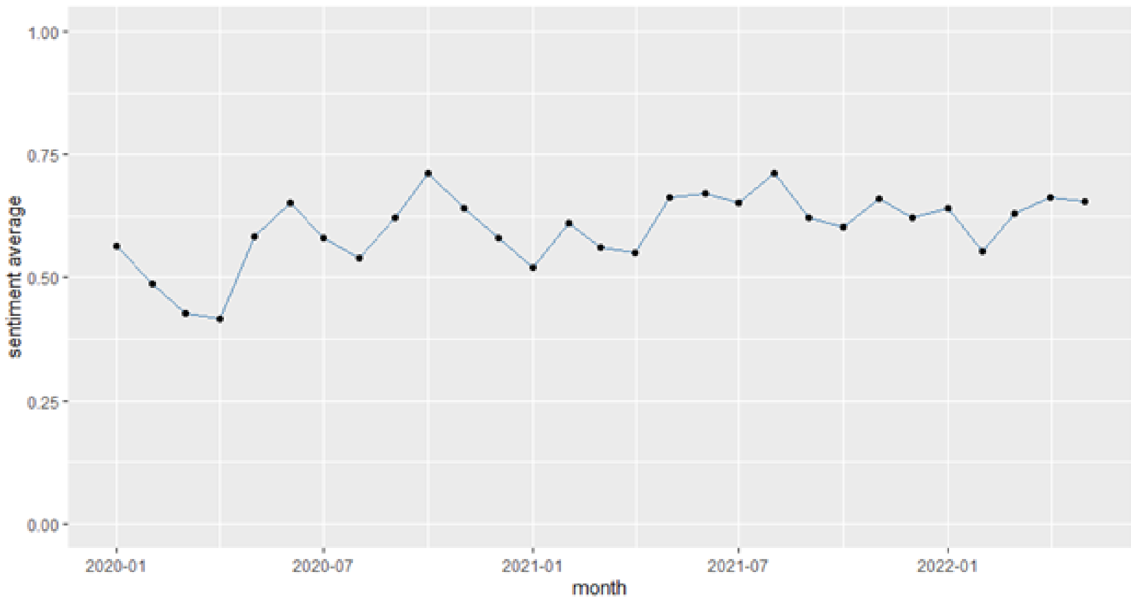


Figure 7: The detailed internals of an LSTM

Training of a LSTM model is similar to other forms of neural networks which involves gradient descent to adjust trainable parameters (Kaur). Pairs of input sentences and labels are fed to the network, where the output produced from forward pass is compared with ground-truth labels. Binary Cross Entropy was used as the loss function for this purpose, as the sentiments are labelled in two classes: positive and negative. The Adam Optimizer was utilized to perform backpropagation, where the weights and biases are updated from the loss calculated.

After the training stage, weights of the model are frozen, and the input data was passed into the trained model to determine their sentiments. Probability of class ‘positive’ was recorded as an input’s sentiment score.

5. Experimental Results



Note: This chart illustrates the average sentiment score in each month from January 1, 2020 to May 31, 2022 in Canada

Figure 8: Time series analysis from January 2020 - May 2022

Figure 8 illustrates the average sentiment score in each month from January 1, 2020 to May 31, 2022 in Canada. In this period the average sentiment score ranges between 0.4 to 0.8. In trying to discover the reason for the change, we coincidentally found another graph which shows the number of deaths caused by Covid-19 in Canada (Figure 9). When death comes to a peak at a certain period, for example, during April 2020, when the sentiment score seems to decline a bit. Conversely, when the death rate is at its lowest level during August 2020, the sentiment scores appear to be at a high level. Therefore, this evidence demonstrates that people’s sentiment and covid’s death rate may have a negative correlation.

Figure 9: Number of deaths caused by Covid-19 in Canada

Moreover, it is ideal that more factors that influence people's sentiment can be figured out. The focus was shifted to another important factor, policy. and try to find the relationship between them. Therefore, the daily average sentiment score and the Canada Containment and Health Index (Oxford Martin School) which indicates the strictness of the policy by a certain formula and did a correlation analysis. By Person correlation formula, the coefficient is 0.1356379 and the p-value is 5.317e-05, which is less than 0.05, which implies the positive correlation between sentiment score and the strictness of policy is significant. However, many outliers have illustrated in the plot. To solve this, an alternative is to divide the policy into 4 categories according to each's strictness.
For the index between 0 and 0.25, the policy is defined as relaxed; For the index between 0.25 to 0.5, it is defined as advisory policy; For the index between 0.5 to 0.75, it fell into the category of moderately strict policy; And, for the index between 0.75 and 1, it is categorized into strict policy. A box plot is created using R to reflect the result (Figure 10).

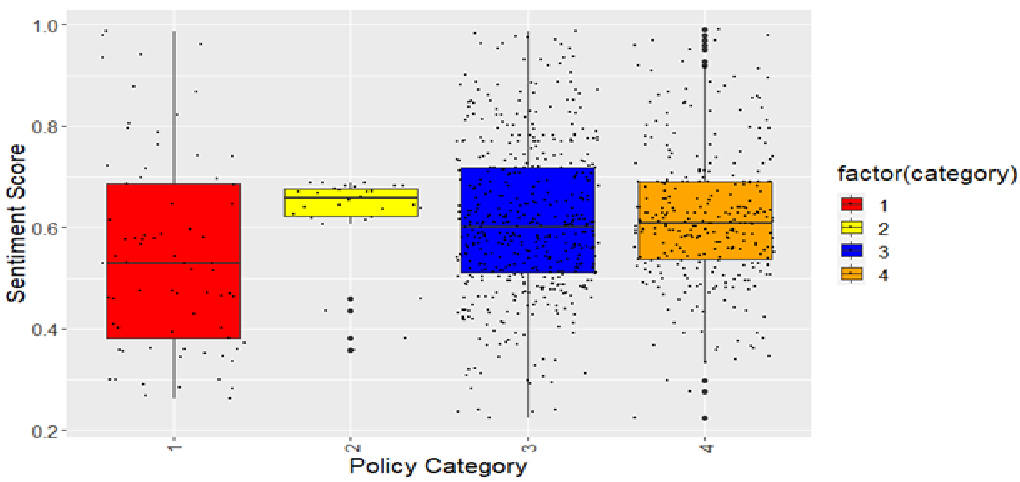


Figure 10: Box plot of policies in Canada

The Figure 10 shows that sentiment score is highest in **Health Advisory** policy (category 2) and lowest in **No Measurement** policy (category 1). Also, for **Regional Lockdown** policy (category 3) and **strict Staying-at-home** policy(category4), cases of people showing extreme sentiment are indicated, a phenomenon that may be caused by the LSTM model's accuracy.

6. Conclusion & Discussion

Reasons underlying people's sentiment change towards Covid-19 can be elusive. Besides the factor of virus nature itself with respect to infection fatality rate, improper government intervention policies also precipitate emotional breakdown. Harsh measures could result in socio-economic collapse meanwhile a relaxed strategy might easily lead to new infection waves or high death toll risk, which makes optimizing this trade-off a highly challenging task. Motivated by this, we demonstrated some of the most significant driving factors that impact people's attitudes towards the pandemic, which is worth consideration for the policy-making process. Indeed, many countries readily incorporated public responses in epidemic preparedness and response systems (Hou et al. 2020). Our findings primarily involve two dimensions:

- Firstly, people's sentiment is influenced by the nature of the virus itself. In compliance with our results, we showed that negative sentiments (e.g. depression, anxiety, and frustration) were directly related to the infection fatality rate. Intuitively, a higher lethality rate denotes danger, which promotes panic and terror. Based on our figures, we showed a strong positive correlation among the two variables. What's worth noticing is that this correlation is indistinct at the initial outbreak of virus, which represents a mix between positive to negative emotions. This could be explained by people's uncertainty in the initial reproduction number and infection fatality rate of virus as a result of misinformed rumors, which only becomes clarified at later phases of pandemic.

- On the other hand, we found that the virus's transmissibility has little relevance with people's sentiment change. More specifically, high transmissibility (e.g. Omicron variant) induced emotional fluctuation, but did not necessarily steer towards a particular positive or negative side.

Another aspect concerns public sector containment actions, in which we used four categories to denote the government stringency level: relaxed, advisory, moderate, strict. Our results suggested that stricter intervention strategies were followed by a more market negative sentiment. While fully relaxed measures were not supported, total lockdowns were completely undesirable, as they create depression. Specifically, advisory and moderate level policy achieved the highest level of sentiment, 0.68 and 0.7 respectively. Besides, when the containment measure is inconsistent with the infection fatality rate of the virus (e.g. complete regional lockdown and compulsory testing rate during a mild virus period), people's negative sentiment soared. This is partially explained by the fact that lack of clarification of rumors and prolonged containment measures led to decreased risk perception towards the virus and prompted fatigue with sustaining policy instructions. This completely contrasted with the former pandemic period in 2020, where studies have shown that despite nationwide lockdown, people expressed trust and gratitude towards their government and increased optimism as time progressed (Barkur et al. 2020; Lyu et al.2020).

To account for this change, we summarized and compared the characteristics of the virus variant and the rigidity of mainstream containment strategy between two periods. In particular, we evaluated the government measure based on a set of indexes, including restriction in public gatherings, public transport, and financial emphasis on testing policy as well as contact tracing. Certainly, the most notable difference lies in the change of prevailing virus nature from 2020 to 2022, where the original one possessed a higher infection lethality rate but lower transmissibility compared with today's Omicron variant. While most countries alleviated their containment system accordingly, a number of countries such as India, Italy, Pakistan, China still maintained a stringency level over 0.85 (fourth category), persisting its rigid measure towards COVID-19 in price of substantial socio-economic costs used in hospitalization, medical care and testing of the symptomatic patients. This could trigger people's emotional evolution towards the pandemic as prolonged deprivation of life quality during lockdown may result in social fatigue and confusion, decreasing the receptiveness towards measure.

7. Future Works

In future works, we plan to extend the framework to account for more regions and countries so we could understand the public's reactions during different epidemic peaks from a more generalized perspective. The sentiment prediction model can also be improved to recognize different dimensions of emotions as our current model is onefold and fails to look at the more complex nature of emotions of the people. Creating classifications of emotions and possibly calculating a weighted average, should allow a more comprehensive interpretation of sentiment changes. Additionally, implementing some state-of-the-art models (such as BERT) through the HuggingFace pipeline can be regarded as the comparison for our proposed model in this paper. Also, it is necessary to use cross-validation methods to prove the stability of the model it the future. Finally, the framework can incorporate topic detection which provides details for emerging topics at different stages of COVID-19. This could bring us new perspectives that may further support current results.

Reference

[1] Agarwal, A., Sharma, V., Sikka, G., & Dhir, R. (2016). Opinion mining of news headlines using SentiWordNet. *2016 Symposium on Colossal Data Analysis and Networking (CDAN)*, 1–5. https://doi.org/10.1109/CDAN.2016.7570949

[2] Angiani, G., Ferrari, L., Fontanini, T., Fornacciari, P., Magliani, F., & Manicardi, S. (n.d.). *A Comparison between Preprocessing Techniques for Sentiment Analysis in Twitter*. 11.

[3] Barkur, G., Vibha, & Kamath, G. B. (2020). Sentiment analysis of nationwide lockdown due to COVID 19 outbreak: Evidence from India. *Asian Journal of Psychiatry*, *51*, 102089. https://doi.org/10.1016/j.ajp.2020.102089

[4] Dubey, A. D. (2020). Twitter Sentiment Analysis during COVID19 Outbreak. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3572023

[5] Garcia, K., & Berton, L. (2021). Topic detection and sentiment analysis in Twitter content related to COVID-19 from Brazil and the USA. *Applied Soft Computing*, *101*, 107057. https://doi.org/10.1016/j.asoc.2020.107057

[6] Gupta, P., Kumar, S., Suman, R. R., & Kumar, V. (2021). Sentiment Analysis of Lockdown in India During COVID-19: A Case Study on Twitter. *IEEE Transactions on Computational Social Systems*, *8*(4), 992–1002. https://doi.org/10.1109/TCSS.2020.3042446

[7] Haddi, E., Liu, X., & Shi, Y. (2013). The Role of Text Pre-processing in Sentiment Analysis. *Procedia Computer Science*, *17*, 26–32. https://doi.org/10.1016/j.procs.2013.05.005

[8] Hou, Z., Du, F., Jiang, H., Zhou, X., & Lin, L. (2020). *Assessment of Public Attention, Risk Perception, Emotional and Behavioural Responses to the COVID-19 Outbreak: Social Media Surveillance in China* (SSRN Scholarly Paper No. 3551338). Social Science Research Network. https://doi.org/10.2139/ssrn.3551338

[9] Kaur, H., Ahsaan, S. U., Alankar, B., & Chang, V. (2021). A Proposed Sentiment Analysis Deep Learning Algorithm for Analyzing COVID-19 Tweets. *Information Systems Frontiers*, *23*(6), 1417–1429. https://doi.org/10.1007/s10796-021-10135-7

[10] Kim, Y., Jernite, Y., Sontag, D., & Rush, A. M. (2015). *Character-Aware Neural Language Models* (arXiv:1508.06615). arXiv. http://arxiv.org/abs/1508.06615

[11] Krishna, A., & Aich, A. (n.d.). *Analysis of Customer Opinion Using Machine Learning and NLP Techniques*. 5.

[12] Lamsal, R. (2021). Design and analysis of a large-scale COVID-19 tweets dataset. *Applied Intelligence*, *51*(5), 2790–2804. https://doi.org/10.1007/s10489-020-02029-z

[13] Lyu, X., Chen, Z., Wu, D., & Wang, W. (2020). Sentiment Analysis on Chinese Weibo Regarding COVID-19. In X. Zhu, M. Zhang, Y. Hong, & R. He (Eds.), *Natural Language Processing and Chinese Computing* (pp. 710–721). Springer International Publishing. https://doi.org/10.1007/978-3-030-60450-9_56

[14] Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113. https://doi.org/10.1016/j.asej.2014.04.011

[15] Moraes, R., Valiati, J., & Gavião Neto, W. (2013). Document-level sentiment classification: An empirical comparison between SVM and ANN. *Expert Systems with Applications*, *40*, 621–633. https://doi.org/10.1016/j.eswa.2012.07.059

[16] Nemes, L., & Kiss, A. (2021). Social media sentiment analysis based on COVID-19. *Journal of Information and Telecommunication*, *5*(1), 1–15. https://doi.org/10.1080/24751839.2020.1790793

[17] Ritchie, H., Mathieu, E., Rodés-Guirao, L., Appel, C., Giattino, C., Ortiz-Ospina, E., Hasell, J., Macdonald, B., Beltekian, D., & Roser, M. (2020). Coronavirus Pandemic (COVID-19). *Our World in Data*. https://ourworldindata.org/covid-stringency-index

[18] Saif, H., Fernandez, M., He, Y., & Alani, H. (n.d.). *On Stopwords, Filtering and Data Sparsity for Sentiment Analysis of Twitter*. 8.

[19] Saravia, E., Liu, H.-C. T., Huang, Y.-H., Wu, J., & Chen, Y.-S. (2018). CARER: Contextualized Affect Representations for Emotion Recognition. *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, 3687–3697. https://doi.org/10.18653/v1/D18-1404

[20] Singh, P., Dwivedi, Y. K., Kahlon, K. S., Sawhney, R. S., Alalwan, A. A., & Rana, N. P. (2019). Smart Monitoring and Controlling of Government Policies Using Social Media and Cloud Computing. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-019-09916-y

[21] Tsao, S.-F., MacLean, A., Chen, H., Li, L., Yang, Y., & Butt, Z. A. (2022). Public Attitudes During the Second Lockdown: Sentiment and Topic Analyses Using Tweets From Ontario, Canada. *International Journal of Public Health*, *0*. https://doi.org/10.3389/ijph.2022.1604658

[22] Wang, Y., Sun, A., Han, J., Liu, Y., & Zhu, X. (2018). Sentiment Analysis by Capsules. *Proceedings of the 2018 World Wide Web Conference*, 1165–1174. https://doi.org/10.1145/3178876.3186015

[23] Zhou, X., Song, Y., Jiang, H., Wang, Q., Qu, Z., Zhou, X., Jit, M., Hou, Z., & Lin, L. (2021). Comparison of Public Responses to Containment Measures During the Initial Outbreak and Resurgence of COVID-19 in China: Infodemiology Study. *Journal of Medical Internet Research*, *23*(4), e26518. https://doi.org/10.2196/26518